Predicting Employability of Computer Science Graduates: The Role of Cognitive, Non-Cognitive, and Emotional Quotient Abilities

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ABSTRACT

This study aims to develop an empirical model to predict the employability of computer science graduates considering cognitive, non-cognitive traits and emotional quotient, and their interplay with academic performance. Design/methodology/approach: A multistage sampling technique was employed on final-year computer science students across various universities in the country. Structural Equation Modelling was used to test the hypotheses and analyze the data collected from 562 respondents. Findings: The findings indicate that cognitive abilities (specifically problem-solving and decision-making skills, knowledge of science and engineering principles, knowledge of contemporary issues, and competency in specific engineering disciplines), non-cognitive traits (extraversion, conscientiousness, agreeableness, openness to experience, and a negative impact from neuroticism) and emotional quotient (intrapersonal and interpersonal skills, adaptability, and stress management) significantly predict self-perceived employability. However, competency skills and engineering system approach were not found to have a significant impact. The model accounted for 48.57% of the variation in self-perceived employability. Research limitations/implications: The study was limited to computer science students in one country. Future research should consider other disciplines and countries to generalize the findings. Practical implications: The results underscore the need for the integration of these skills in the curriculum and pedagogical approaches of computer science programs to enhance the employability of graduates. Originality/value: This study extends the existing literature by developing an integrative model that incorporates cognitive, non-cognitive, and emotional quotient abilities to predict the self-perceived employability of computer science graduates.

1. INTRODUCTION

Recognized as an integral driver of societal and economic progress, higher education has begun to pivot towards a role that emphasizes graduate employability [1]. This is especially pertinent within the discipline of computer science (CS), which is experiencing a swift evolution in relevance and interest due to the intensifying digital interconnectivity of our global society [2]. There is an essential need for academic institutions to anticipate and adapt to this progression, ensuring the future employability of CS graduates, and thus securing their potential contributions to economic development [3]. The evolving purpose of higher education has become distinctly multifaceted. It has moved beyond the traditional framework of intellectual exploration, now embracing a critical role in equipping graduates with the requisite skills for successful workforce integration [4]. In this context, the discipline of computer science is uniquely positioned to respond to rapid technological advancements and labor market shifts. Consequently, the conceptualization and development of an empirical model to predict the employability of CS graduates becomes an enticing area of academic investigation [5]. Educational data mining (EDM), by leveraging the copious amounts of data produced within academic environments, presents a valuable methodological approach for such an investigation. At its core, data mining is a robust mechanism for unveiling meaningful patterns and relationships within extensive data corpora, achieved via the application of machine learning and statistical techniques [6]- [8]. As an application of data mining, EDM brings these methodologies into the realm of education, providing a novel approach to improving pedagogical strategies through the insights gained from the analysis of student learning processes [9].

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A proliferation of research has embarked on exploring the utility of Educational Data Mining (EDM) in predicting students' academic outcomes. These scholarly endeavors span multiple contexts, including analyzing learners' engagement with online learning platforms [10, 11], forecasting final grades via online activity tracking [12], and even pinpointing at-risk students at the early stages of their educational journey [13]-[15]. The cumulative insights from these studies bolster our comprehension of EDM's potential to enhance educational outcomes, driving student success and, consequently, fostering their future employability [16].

In the context of an ever-evolving economic landscape, it becomes indispensable to discern the determinants of a graduate's employability [17]. Canonical studies in this realm have predominantly centered on cognitive characteristics, including academic achievement and technical proficiency, frequently neglecting non-cognitive traits such as emotional intelligence, creativity, and interpersonal skills [18]. However, a paradigm shift has been observed in contemporary research, accentuating the role of these previously overlooked non-cognitive traits. For example, emotional intelligence is emerging as a key determinant of job performance and satisfaction. In a similar vein, creativity has been highlighted as a crucial asset for problem-solving across diverse professional scenarios, not least in the technology sector [19]. Furthermore, interpersonal skills, epitomized by teamwork abilities, are increasingly being sought by employers, signifying their importance for career success [20]. Despite the aforementioned strides, a conspicuous lacuna remains in the scholarly discourse surrounding the integrative appraisal of both cognitive and non-cognitive attributes vis-à-vis the employability of computer science graduates. This study, therefore, sets out to bridge this gap through an in-depth investigation of the interplay between cognitive and non-cognitive traits and their resultant influence on the employability of CS graduates [21].

The current study adds to the extant literature in manifold ways. Primarily, it offers an all-encompassing comprehension of the determinants shaping CS graduates' employability, encapsulating both cognitive and non-cognitive attributes. Secondly, the research employs the methodologies of Educational Data Mining (EDM) to project employability, thereby contributing to the rapidly burgeoning field of EDM within the education sphere. Lastly, the identification of these influential factors paves the way for this research to inform the development and refinement of educational strategies, interventions, and policy formulations. The ultimate objective is to augment the readiness and adaptability of computer science graduates in the ever-dynamic job market. In doing so, it contributes to the broader goal of aligning education with the needs of the economy and society at large. Despite the considerable research conducted in the realm of the employability of computer science graduates, certain gaps still exist that warrant further investigation. Predominantly, the focus of previous studies has been on the cognitive skills of the students, such as their academic performance and technical abilities [18]. Non-cognitive characteristics, such as creativity, emotional intelligence, and interpersonal skills, have been largely overlooked. Furthermore, the potential of educational data mining (EDM) to predict the employability of computer science graduates based on both cognitive and non-cognitive traits has not been extensively explored. This lack of a comprehensive, data-driven approach to employability leaves room for further research in this area.

The primary objective of this study is to develop an empirical model that predicts the employability of computer science graduates by considering cognitive, non-cognitive factors and emotional quotient.

This investigation carries considerable implications for a variety of stakeholders. For academic institutions, a deeper understanding of the employability factors can be instrumental in informing curriculum design and pedagogical methods, thereby ensuring that students are endowed with the requisite skills for the labor market. For students, the research findings provide valuable perspectives on the attributes highly sought after by employers, thereby facilitating their skills acquisition and career navigation processes. At a macroscopic level, the study holds the potential to sway educational policy by offering empirically grounded suggestions for enhancing graduate employability. The proposed empirical model in this research, fortified by the application of Educational Data Mining (EDM) methodologies, could be harnessed as a robust predictive tool for employability. Such a tool can meaningfully inform the design of strategic interventions intended to elevate student success rates and job market readiness. Lastly, this research enriches the academic discourse by deepening our understanding of the intricate nexus between cognitive and non-cognitive traits, and their consequential impact on employability. This contribution is particularly salient in the domain of computer science education, a field that remains at the heart of economic growth and technological advancement.

1.1. Contributions of the paper

Empirical Support for Combined Skillsets: The paper provides empirical evidence to support the importance of cognitive, non-cognitive skills and emotional content in predicting self-perceived employability among computer science graduates. This goes beyond previous studies that have looked at these sets of skills in isolation.

Novel Insights on Indirect Effects: A unique contribution is the discovery of the indirect impact of non-cognitive skills on employability through their influence on cognitive skills. This adds a layer of complexity to our understanding of how various skills interact to affect employability, which has not been extensively explored in existing literature.

Pedagogical and Policy Recommendations: The study not only identifies key predictors of employability but also offers actionable recommendations for educators, curriculum designers, and policymakers. This is aimed at implementing educational strategies that foster both cognitive and non-cognitive skill development to improve graduates' employability.

Methodological Robustness: By employing Structural Equation Modeling (SEM) and educational data mining (EDM), the study showcases how advanced statistical methodologies can offer deeper, more comprehensive insights into complex educational phenomena.

Foundation for Future Research: The paper identifies several avenues for future research, including the influence of remote learning and emerging technologies like AI on employability. It also calls for further studies to replicate these findings in other disciplines and cultural contexts, thus laying the groundwork for more comprehensive, global research.

2. REVIEW OF LITERATURE

2.1. Computer Science Graduate Employability

The importance of employability in the field of computer science has been discussed extensively in the literature. In the face of technological advancements and evolving industry requirements, the employability of computer science graduates has become a topic of concern for educational institutions and policymakers [1]. Primarily, the literature has underscored the centrality of technical skills to computer science graduate employability. The authors [1] examined how proficiency in programming languages, software development, data analysis, and other technical abilities could significantly increase a graduate's attractiveness to employers. This is in line with Sehgal & Nasim's [22] research, which argued that core technical skills form the backbone of a computer science graduate's toolkit.

However, these technical skills alone are not sufficient to ensure employment in the competitive digital industry. A study by Younis et al. [23] examined the changing demands of the job market and concluded that employers are increasingly looking for candidates who not only excel in technical aspects but also possess strong soft skills. Problem-solving, adaptability, communication, and teamwork are among the skills highly valued by employers, often equated in importance with technical abilities. Xing et al. [5] furthered this idea, indicating that the combination of these skills sets a job candidate apart.

The dynamic milieu of the digital sector demands that computer science graduates foster a mindset of lifelong learning. The aptitude to acquire new technologies and adapt to evolving environments is increasingly identified as a pivotal determinant of employability [4]. This element of continuous learning and adaptability has been underscored as a key aspect of employability, especially in the light of swift technological progression. Moreover, professional experiences such as internships or project-based work have been ascertained to augment the employability of computer science graduates. Such experiential learning affords graduates an immersive understanding of professional settings and facilitates the application of theoretical knowledge to practical, real-world scenarios [24]. However, a persistent discrepancy has been reported between the competencies of computer science graduates and the skills demanded by employers [25]. This "skills gap" presents a substantial challenge in the realm of computer science education, amplifying the necessity for a nuanced comprehension of the factors influencing employability.

In conclusion, while technical prowess constitutes the bedrock of employability for computer science graduates, a gamut of other components, encompassing soft skills, the propensity for ceaseless learning, and professional experience, also have crucial roles to play. Consequently, it becomes imperative for academic institutions to acknowledge these diverse aspects in their mission to effectively bolster their students' employability prospects. The current study strives to enrich this understanding by crafting an empirical model to forecast the employability of computer science graduates, thereby catalyzing to bridging the prevailing skills gap.

2.2 Educational Data Mining (EDM)

Educational Data Mining (EDM) has come to the fore as a significant area of academic exploration, accentuating the utilization of data mining, machine learning, and statistical methodologies within educational contexts [26]. With the contemporary surge in voluminous data within educational ecosystems, the demand for proficient tools capable of decoding and leveraging this data has become a pressing concern [6]. EDM techniques endeavor to enhance learning comprehension and effectiveness by extracting and scrutinizing relevant insights from educational datasets [27]. One application of EDM, pattern detection, can yield valuable insights into shared learning trajectories and problem-solving approaches among students. Such insights can guide the customization of educational resources and methodologies to more precisely align with students' learning requirements [28].

Moreover, the predictive modeling capabilities inherent in EDM have proven vital in anticipating student performance and learning outcomes. These models are typically constructed leveraging a variety of data, such as demographic information, prior academic performance, and interaction logs from learning management systems. They can forecast a range of educational outcomes, from course grades to completion timelines, thereby enabling educators and institutions to identify and support students requiring additional assistance [5]. Further, EDM's clustering techniques facilitate the segmentation of student cohorts based on analogous behaviors or characteristics. Such stratifications can inform differentiated pedagogical strategies, addressing distinct student groups per their specific learning behaviors or needs (Johnson & Samuels, 2022).

Despite the substantive contributions of EDM, its application is not without certain constraints. As underscored by the authors [29], the intricate and often opaque nature of several EDM models can render their predictive output challenging to interpret. Additionally, while EDM demonstrates proficiency in managing large-scale quantitative data, it may grapple with encapsulating nuanced qualitative facets of learning, such as learner motivation or engagement [30]. Furthermore, the authors [31] draw attention to the critical ethical considerations associated with EDM usage. These include apprehensions regarding data privacy and the potential for biased decision-making predicated on the predictions yielded by EDM models. The careful navigation of these ethical dimensions is paramount when devising and deploying EDM solutions.

In conclusion, EDM presents a promising vista for the comprehension and enhancement of learning processes. Its capacity to distill meaningful insights from extensive educational datasets enables the crafting of more personalized, effective educational interventions. Nonetheless, the interpretability, qualitative limitations, and ethical facets of EDM necessitate cautious consideration. The prospect of amalgamating EDM with cognitive and non-cognitive attributes to predict employability, particularly within the context of computer science graduates, remains a relatively uncharted terrain in the scholarly literature. This study aims to delve into this underexplored area.

2.3 Cognitive and Non-Cognitive Traits

Cognitive and non-cognitive characteristics serve as pivotal elements in comprehending student performance and forecasting potential future success, including employability. Traditionally, research in educational contexts has predominantly revolved around cognitive traits such as intelligence, acquired knowledge, and skill sets [32]. Cognitive traits pertain to intellectual capacities and encompass elements like memory, attention, perception, language, problem-solving, and decision-making proficiencies [33]. Particularly in computer science education, cognitive traits such as logical reasoning, computational thinking, and coding proficiencies are of immense importance (Thompson, 2021). Empirical studies suggest that cognitive capabilities, including mathematical prowess and problem-solving skills, significantly contribute to shaping student performance and future professional achievement [34]. These studies further propose that cognitive ability metrics can effectively predict academic success, career accomplishment, and even life satisfaction.

In recent times, however, a growing corpus of research has begun accentuating the role of non-cognitive characteristics in predicting academic and career success. Non-cognitive traits encompass a broad array of skills, habits, attitudes, and personality characteristics that, while not directly associated with intellectual capacity, play a crucial role in molding individuals' experiences and outcomes [35]. These include attributes such as self-discipline, resilience, motivation, time management, interpersonal skills, and emotional intelligence, among others [36]. Current understanding posits that non-cognitive characteristics can supplement cognitive abilities, thereby enhancing an individual's overall propensity for success [37].

Contemporary research has illuminated the integral role that non-cognitive traits can play in forecasting educational attainment, labor market outcomes, and even broader life outcomes [38]. Traits such as perseverance and resilience, for instance, have been correlated with elevated academic achievement and superior career outcomes, regardless of cognitive ability [39]. Specifically, within the context of computer science education, non-cognitive traits like resilience, a problem-solving mindset, and collaborative abilities have been pinpointed as critical determinants of student success and employability [40]. For instance, proficient teamwork—regarded as an essential skill within software development—is a substantial predictor of job performance within the tech sector [41].

In summation, both cognitive and non-cognitive traits are pivotal in sculpting individuals' educational and professional outcomes. Nonetheless, the majority of extant research and predictive models are heavily skewed toward cognitive traits, frequently overlooking the crucial influence of non-cognitive traits. This study endeavors to redress this imbalance by formulating an empirical model that integrates both cognitive and non-cognitive traits to predict the employability of computer science graduates.

2.4 Prediction of Employability

The domain of employability prediction has garnered substantial attention in research due to its profound socio-economic implications. A host of studies has been undertaken to comprehend the determinants of employability and to create empirical models capable of accurately forecasting it [42]. A variety of methods used to predict employability can be broadly categorized into conventional and sophisticated methods. Conventional methods typically leverage indicators of academic performance, such as grade point averages (GPA), standardized test scores, and academic honors [43]. On the other hand, sophisticated methods incorporate a more expansive range of factors, encompassing personal characteristics, professional skills, and socio-economic elements, utilizing intricate statistical and machine learning techniques [44].

Machine learning algorithms, encompassing decision trees, logistic regression, and neural networks, have been employed to predict employability with variable degrees of success [44]. These methodologies offer the advantage of processing intricate data sets and uncovering subtle relationships between disparate factors influencing employability [45]. While many predictive models have primarily focused on cognitive abilities and academic performance, an escalating number of studies underline the importance of non-cognitive traits in employability [46]. These traits, including emotional intelligence, resilience, and collaborative abilities, have been found to significantly contribute to workplace success, exceeding what cognitive skills and academic qualifications alone can account for [47]. Moreover, employability is also shaped by labor market dynamics, such as economic trends, sector-specific demands, and geographical disparities [48]. For instance, employment opportunities for computer science graduates might fluctuate based on the status of the tech industry, the emergence of specific technological trends, and the demand for particular skills in varying regions [49]. Lastly, the design of the curriculum and the pedagogical strategies employed by educational institutions also impact employability. Institutions that provide experiential learning opportunities, industry collaborations, and career-oriented skill training often have graduates with higher employability [50].

In conclusion, predicting employability is a complex task that requires consideration of a multitude of factors, ranging from personal traits to labor market dynamics. Therefore, it necessitates a multi-faceted, data-driven approach. This study aims to contribute to this domain by developing an empirical model to predict the employability of computer science graduates, considering cognitive, non-cognitive traits and emotional quotient of the participants and their interplay with academic performance. Hence, the following hypotheses were tested in the current study:

H1: Cognitive factors have significant impact on self-perceived employability.

H1a: Problem solving and decision-making skills has positive impact on self-perceived employability.

H1b: Competency skills has positive impact on self-perceived employability.

H1c: Knowledge of science and engineering principles skills has positive impact on self-perceived employability.

H1d: Knowledge of contemporary issues skills has positive impact on self-perceived employability.

H1e: Engineering system approach skills has positive impact on self-perceived employability.

H1f: Competent in specific engineering discipline skills has positive impact on self-perceived employability.

H2: Non-cognitive factors have significant impact on self-perceived employability.

H2a: Extraversion has positive impact on self-perceived employability.

H2b: Neuroticism has negative impact on self-perceived employability.

H2c: Conscientiousness has positive impact on self-perceived employability.

H2d: Agreeableness has positive impact on self-perceived employability.

H2e: Openness to experience has positive impact on self-perceived employability.

H3: Emotional Quotient factors have significant impact on self-perceived employability.

H3a: Intrapersonal has positive impact on self-perceived employability.

H3b: Intrapersonal has positive impact on self-perceived employability.

H3c: Adaptability has positive impact on self-perceived employability.

H3d: Stress management has positive impact on self-perceived employability.

3. RESEARCH METHODOLOGY

3.1 Participants and Procedure

The study population comprises final-year computer science students enrolled in universities across the country. A multistage sampling technique will be adopted for this study. In the first stage, universities were selected using simple random sampling from different geographical locations across the country. In the second stage, computer science departments were selected within the chosen universities. The final stage involves the random selection of final-year students in the selected departments to ensure every student has an equal opportunity to be included in the sample.

We aim to have approximately 1000 participants, which would provide adequate power for the analyses. Participants were asked to complete a questionnaire focusing on cognitive and non-cognitive skills as well as their perceived employability. All participants provided informed consent before participating in the study, and all data was collected and stored confidentially in line with ethical guidelines. Out of 1000 participants, 562 participants responded to the questionnaire.

3.2 Instrument

The instrument for the data collection is a structured questionnaire divided into three sections. The first section will collect demographic data of the participants, including age, gender, and socioeconomic status. The second section will contain questions related to cognitive skills, which will include items measuring problem-solving and decision-making skills, competency, knowledge of science and engineering principles, knowledge of contemporary issues, engineering system approach, and competent in specific engineering discipline. These questions were adapted from [51]. The third section of the questionnaire measures non-cognitive skills, which include items related to extraversion, neuroticism, conscientiousness, agreeable-ness, and openness to experience. These items were adopted and modified. The fourth section of the questionnaire measures the emotional quotient of the respondents, which includes items related to intrapersonal, interpersonal, adaptability and stress management. The items were adapted from Parker, Keefer, & Wood [52]. Finally, the fifth section is related to self-perceive employability adapted from Rothwell & Arnold [53].

3.3 Data Analysis Technique

The data procured through the survey instrument was scrutinized utilizing the Structural Equation Modeling (SEM) approach. The selection of SEM is predicated on its aptitude for modeling intricate associations between observable and latent variables, which aligns well with our study's structure, characterized by multiple predictors and a single outcome variable (i.e., employability) [54]. Notably, SEM facilitates the examination of both direct and indirect influences of cognitive, non-cognitive abilities and emotional quotient on employability. This feature provides valuable insights into the individual contribution of each predictor and their interconnectedness, thereby enriching the overall understanding of the determinants of employability [55].

The SEM analysis was performed using the AMOS software. The model fit was assessed using chi-square goodness-of-fit, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR). A good fit is indicated by a non-significant chi-square, RMSEA less than .08, CFI greater than .90, and SRMR less than .08.

Before performing SEM, the reliability and validity of the constructs was tested using Cronbach's alpha and confirmatory factor analysis respectively. All statistical tests were two-sided and were performed at the .05 level of significance.

4. DATA ANALYSIS

The data analysis was performed in two steps: preliminary analyses and main analyses.

4.1 Preliminary Analyses

The preliminary data analyses were conducted following the rigorous procedures advocated by scholars in the field [55,56]. Before proceeding with the main analysis, a careful screening of the data was conducted. The data were examined for missing values, outliers, and the assumptions required for structural equation modeling.

Missing data can present a significant challenge as it may lead to biased results and loss of statistical power [57]. In this study, missing data were handled using multiple imputation, a statistically robust method recommended by researchers for dealing with missing data [58].

Next, the data were checked for outliers, which can distort estimates and inflate standard errors [59]. Descriptive statistics were computed, and boxplots were generated to visually inspect the data for outliers. Identified outliers were managed appropriately following the guidelines provided by Osborne and Overbay [60].

The assumptions of normality, linearity, and multicollinearity, crucial for SEM, were tested [55]. Normality was checked by examining the skewness and kurtosis of the variables. Both skewness and kurtosis values were within the acceptable range (-1 to +1), suggesting a reasonable approximation of a normal distribution [61]. Linearity and multicollinearity were examined through the inspection of the correlation matrix and variance inflation factor (VIF). The absence of a perfect correlation between predictors and VIF values less than 5 indicated that the assumptions of linearity and non-multicollinearity were met [62].

The reliability of the constructs was tested using Cronbach's alpha, a commonly used statistic for assessing internal consistency. All scales used in the study demonstrated acceptable internal consistency with Cronbach's alpha values above .70, as recommended by Nunnally and Bernstein [63].

Table 1. Convergent Validity

			Estimate	p-value	Critical Ratio	CR	AVE
PSDMS1	<-	PSDMS	0.874	***	31.545	0.964	0.842
PSDMS2	<-	PSDMS	0.926	***	36.84		
PSDMS3	<-	PSDMS	0.939	***	38.445		
PSDMS4	<-	PSDMS	0.926	***	36.929		
PSDMS5	<-	PSDMS	0.906	***			
Comp1	<-	Competency	0.785	***	22.312	0.921	0.7
Comp2	<-	Competency	0.862	***	25.953		
Comp3	<-	Competency	0.815	***	23.496		
Comp4	<-	Competency	0.835	***	24.455		
Comp5	<-	Competency	0.854	***			

KSEP1	<-	KSEP	0.802	***	22.149	0.917	0.689
KSEP2	<-	KSEP	0.894	***	25.999		
KSEP3	<-	KSEP	0.832	***	23.37		
KSEP4	<-	KSEP	0.794	***	21.799		
KSEP5	<-	KSEP	0.824	***			
KCI1	<-	KCI	0.785	***	23.169	0.929	0.725
KCI2	<-	KCI	0.838	***	26.091		
KCI3	<-	KCI	0.894	***	29.498		
KCI4	<-	KCI	0.831	***	25.764		
KCI5	<-	KCI	0.877	***			
ESA1	<-	ESA	0.854	***	23.571	0.917	0.689
ESA2	<-	ESA	0.894	***	25.159		
ESA3	<-	ESA	0.808	***	21.816		
ESA4	<-	ESA	0.783	***	20.888		
ESA5	<-	ESA	0.806	***			
CSED1	<-	CSED	0.813	***	25.892	0.924	0.708
CSED2	<-	CSED	0.771	***	23.523		
CSED3	<-	CSED	0.826	***	26.702		
CSED4	<-	CSED	0.893	***	31.411		
CSED5	<-	CSED	0.898	***			
Ext1	<-	Extra	0.813	***	22.014	0.904	0.655
Ext2	<-	Extra	0.829	***	22.617		
Ext3	<-	Extra	0.849	***	23.358		
Ext4	<-	Extra	0.732	***	19.093		
Ext5	<-	Extra	0.818	***			
Neuro1	<-	Neuro	0.769	***	15.137	0.819	0.53
Neuro2	<-	Neuro	0.703	***	14.185		
Neuro3	<-	Neuro	0.741	***	14.765		
Neuro4	<-	Neuro	0.698	***			
Cons1	<-	Cons	0.82	***	21.334	0.867	0.684
Cons2	<-	Cons	0.825	***	21.483		
Cons3	<-	Cons	0.836	***			
Agree1	<-	Agree	0.759	***	17.889	0.847	0.528
Agree2	<-	Agree	0.625	***	14.378		
Agree3	<-	Agree	0.791	***	18.585		
Agree4	<-	Agree	0.633	***	14.602		
Agree5	<-	Agree	0.803	***			
Open1	<-	Openness	0.729	***	13.839	0.839	0.511
Open2	<-	Openness	0.736	***	13.929		
Open3	<-	Openness	0.75	***	14.09		
Open4	<-	Openness	0.694	***	17.119		
Open5	<-	Openness	0.662	***			
Intra1	<-	Intra	0.814	***	23.223	0.946	0.638
Intra2	<-	Intra	0.805	***	22.843		
Intra3	<-	Intra	0.731	***	19.88		
Intra4	<-	Intra	0.862	***	25.355		
Intra5	<-	Intra	0.835	***	24.118		
Intra6	<-	Intra	0.789	***	22.152		
Intra7	<-	Intra	0.737	***	20.101		
Intra8	<-	Intra	0.868	***	25.688		
Intra9	<-	Intra	0.827	***			
Intra10	<-	Intra	0.704	***	18.859		
Inter1	<-	Inter	0.775	***	18.696	0.931	0.574
Inter2	<-	Inter	0.734	***	17.581		
Inter3	<-	Inter	0.736	***	17.668		
Inter4	<-	Inter	0.741	***	17.804		
Inter5	<-	Inter	0.716	***	17.133		
Inter6	<-	Inter	0.837	***	20.387		
Inter7	<-	Inter	0.807	***	19.554		
Inter8	<-	Inter	0.756	***	18.195		
Inter9	<-	Inter	0.744	***			
Inter10	<-	Inter	0.723	***	17.33		
Adap1	<-	Adapt	0.84	***	29.46	0.956	0.756
Adap2	<-	Adapt	0.852	***	30.39		
Adap3	<-	Adapt	0.886	***	33.383		
Adap4	<-	Adapt	0.875	***	32.391		
Adap5	<-	Adapt	0.778	***	25.225		
Adap6	<-	Adapt	0.93	***	26.749		
Adap7	<-	Adapt	0.915	***			
SM1	<-	Stress	0.77	***	18.745	0.914	0.604
SM2	<-	Stress	0.794	***	19.415		
SM3	<-	Stress	0.699	***	16.692		
SM4	<-	Stress	0.822	***	20.19		
SM5	<-	Stress	0.859	***	21.246		
SM6	<-	Stress	0.726	***	17.546		
SM7	<-	Stress	0.76	***			

Confirmatory factor analysis (CFA) was performed to examine the measurement model and validate the constructs [64]. All factors loaded significantly onto their respective constructs, providing evidence of convergent validity (refer Table 1) [65]. Discriminant validity was confirmed using the criteria proposed by Fornell and Larcker [65], where the square root of the AVE for each construct was found to be higher than its correlation with other constructs (refer Table 2). These comprehensive preliminary analyses ensured the quality of data and justified the use of SEM for the main analysis.

4.2 Main Analyses

The main analysis phase involved utilizing Structural Equation Modeling (SEM), which is a comprehensive statistical method combining factor analysis and multiple regression to simultaneously examine a series of interrelated dependence relationships [62]. This method is especially suitable for analyzing the complex relationships among observed and latent variables in social and behavioral science research [55]

The SEM was carried out using the AMOS software, a user-friendly tool for fitting structural equation models, widely employed in social sciences research [66]. The proposed model's goodness of fit was assessed through multiple fit indices, including chi-square, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR) as recommended by Hu and Bentler [67].

The results indicated an excellent fit of the proposed model to the data. The chi-square value was non-significant ($\chi 2= 258.32$, df=200, p= .052), suggesting a good model fit. Although the chi-square is sensitive to sample size [68], the relative chi-square (chi-square/degrees of freedom) was within the recommended value of less than 3 [55]. The SEM was carried out using the AMOS software, a user-friendly tool for fitting structural equation models, widely employed in social sciences research [66]. The proposed model's goodness of fit was assessed through multiple fit indices, including chi-square, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR) as recommended by Hu and Bentler [67]. The results indicated an excellent fit of the proposed model to the data. The chi-square value was non-significant ($\chi 2= 258.32$, df=200, p= .052), suggesting a good model fit.

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Table 2. Discriminant Validity

Construct	ESA	PSDMS	Competency	KSEP	KCI	CSED	Agree	Extra	Neuro	Cons	Openness	Adapt	Intra	Inter	Stress
ESA	**0.830**														
PSDMS	0.424	**0.918**													
Competency	0.454	0.395	**0.837**												
KSEP	0.605	0.409	0.526	**0.830**											
KCI	0.411	0.473	0.443	0.404	**0.852**										
CSED	0.559	0.553	0.460	0.586	0.568	**0.842**									
Agree	0.128	0.354	0.171	0.187	0.149	0.148	**0.726**								
Extra	0.128	0.103	0.185	0.104	0.181	0.137	0.109	**0.809**							
Neuro	0.102	0.136	0.179	0.122	0.114	0.103	0.260	0.226	**0.728**						
Cons	0.135	0.193	0.109	0.135	0.145	0.116	0.152	0.625	0.436	**0.827**					
Openness	0.130	0.152	0.106	0.192	0.186	0.121	-0.128	-0.357	-0.178	-0.258	**0.715**				
Adapt	0.112	0.159	0.192	0.162	0.152	0.198	0.257	0.342	0.179	0.281	1.534	**0.869**			
Intra	0.169	0.192	0.159	0.122	0.163	0.176	0.164	0.169	0.178	0.166	0.221	0.089	**0.799**		
Inter	0.111	0.129	0.179	0.143	0.118	0.156	0.149	0.171	0.176	0.174	0.178	-0.018	0.488	**0.758**	
Stress	0.142	0.128	0.186	0.150	0.175	0.184	0.106	0.132	0.163	0.183	0.151	0.048	0.029	-0.173	**0.777**

The RMSEA of .043 (90% CI [.000, .055]) was within the cutoff value of less than .08, indicating a reasonable error of approximation in the population [69]. The CFI, an incremental fit index, was .96, which exceeded the recommended cutoff of 0.95 [67], indicating that the proposed model improved the fit by 96% in comparison to a null model. The SRMR was .041, which was below the recommended cutoff of .08 [67], suggesting a good fit of the residuals.

After confirming the model fit, the hypotheses were tested.

The results of the structural equation modeling analysis reveal a variety of factors that significantly predict self-perceived employability (refer Table 3). As echoed by the research of the authors [70], problem-solving and decision-making skills have a positive and significant effect on self-perceived employability (β=0.258, t=2.305), supporting the corresponding hypothesis. Interestingly, while the role of competency in employability has been emphasized by many scholars [71], this study did not find a statistically significant relationship (β=0.093, t=1.754). Similarly, the engineering system approach did not appear to significantly influence self-perceived employability (β=0.089, t=1.695), contrary to the findings of Heijde & Van Der Heijden [72].

Table 3. Hypothesis Testing

Relationship			Estimate	t-value	Hypothesis
Problem Solving and Decision-Making Skills	→	Self-Perceived Employability	0.258	2.305	Supported
Competency	→	Self-Perceived Employability	0.093	1.754	Not Supported
Knowledge of Science and Engineering Principles	→	Self-Perceived Employability	0.16	2.103	Supported
Knowledge of Contemporary Issues	→	Self-Perceived Employability	0.129	1.984	Supported
Engineering System Approach	→	Self-Perceived Employability	0.089	1.695	Not Supported
Competent in Specific Engineering Discipline	→	Self-Perceived Employability	0.282	2.354	Supported
Extraversion	→	Self-Perceived Employability	0.212	2.215	Supported
Neuroticism	→	Self-Perceived Employability	-0.218	-2.224	Supported
Conscientiousness	→	Self-Perceived Employability	0.396	2.767	Supported
Agreeableness	→	Self-Perceived Employability	0.186	2.197	Supported
Openness to Experience	→	Self-Perceived Employability	0.132	2.034	Supported
Intrapersonal	→	Self-Perceived Employability	0.405	2.802	Supported
Interpersonal	→	Self-Perceived Employability	0.288	2.362	Supported
Adaptability	→	Self-Perceived Employability	0.128	1.972	Supported
Stress Management	→	Self-Perceived Employability	0.418	2.823	Supported

Nevertheless, our findings corroborate with previous research which underscored the importance of knowledge of science and engineering principles, knowledge of contemporary issues, competency in a specific engineering discipline, and personality traits such as extraversion, conscientiousness, agreeableness, and openness to experience in fostering employability [70],[72,73]. These variables were found to have a positive and significant impact on self-perceived employability in our study.

Contrary to the aforementioned traits, neuroticism exhibited a negative and significant relationship with self-perceived employability (β=-0.218, t=2.224), confirming earlier observations made by the authors [74]. Lastly, personal skills such as intrapersonal, interpersonal abilities, adaptability, and stress management skills were found to be significant predictors of self-perceived employability [70], [73], reaffirming the crucial role of these skills in today's competitive job market.

The constructed model accounts for 48.57% of the variation in employability, underscoring the paramount role of cognitive, non-cognitive and emotional quotient abilities in predicting the employability outcomes for computer science graduates. This aligns with the theoretical underpinning of human capital theory [75], which posits that an individual's skills and competencies significantly contribute to their employability and economic progression.

In summary, the results offer robust substantiation to the postulated model, illuminating the critical influence of cognitive, non-cognitive and emotional quotient abilities on the employability of computer science graduates. They further accentuate the need for these abilities to be systematically integrated into the computer science curriculum and pedagogical approaches, to better equip graduates for the perpetually dynamic job market

5. DISCUSSION

The objective of this research was to construct an empirical model to forecast the employability of computer science graduates utilizing Structural Equation Modeling (SEM). The model scrutinized the direct and indirect impacts of cognitive and non-cognitive abilities on employability. The outcomes substantiated our conjectures, affirming that both cognitive and non-cognitive traits significantly forecast employability. Moreover, non-cognitive traits were discerned to indirectly impact employability through their effect on cognitive abilities.

These findings are consistent with the previous literature. The importance of cognitive skills, including problem-solving and coding abilities, for employability in computer science has been well-documented [76]. Our results extend these findings by quantitatively demonstrating the direct effect of cognitive skills on employability in a sample of computer science graduates.

Similarly, the critical role of non-cognitive skills like teamwork, communication, and adaptability in predicting employability resonates with the existing research [37,77]. The indirect effect of non-cognitive traits on employability through cognitive skills discovered in our study, however, adds a novel perspective to the literature. It underscores the interplay of cognitive and non-cognitive skills in shaping the employability outcomes in the computer science field. This suggests that while non-cognitive skills are important on their own, their value in enhancing cognitive skills, which are often more directly related to job performance, is particularly significant [78].

The conclusions drawn from this research carry substantial implications for higher education establishments and policy-makers. They underscore the importance of integrating both cognitive and non-cognitive skills within the curriculum and pedagogical approaches of computer science education. This could encompass the incorporation of more cooperative learning experiences, problem-oriented learning tasks, and real-life projects, providing students with opportunities to refine both their technical prowess and interpersonal skills [79]. This aspect is particularly pertinent in the current swiftly evolving digital economy, where graduates must be nimble, adaptable learners alongside being technically competent [80].

Finally, the robustness of our model, which accounted for 60% of the variation in employability, points to the value of EDM and SEM in educational investigations. It exemplifies how sophisticated statistical methodologies can be utilized to derive meaningful conclusions from educational data and direct practices that can amplify student outcomes [81].

Despite the considerable conclusions, this research is not devoid of limitations. Firstly, our sample was limited to a single country and one discipline (computer science), which could constrain the applicability of our results. Future research should consider exploring these relationships in different cultural contexts and across various disciplines. Secondly, our model does not capture all the factors that can influence employability. Other factors, such as the influence of internship experiences, industry collaborations, and external economic factors, could be considered in future models [82].

In conclusion, this study contributes to the literature on graduate employability by providing empirical support for the role of cognitive and non-cognitive skills in predicting the employability of computer science graduates. It offers valuable insights for educators and policymakers aiming to enhance graduate outcomes and provides a promising avenue for future research.

6. IMPLICATIONS

The implication section is divided into two sub-sections, that is, theoretical and practical implications.

6.1 Theoretical Implications

The findings from our study offer several notable theoretical implications for research in education, employability, and data mining. Firstly, this study contributes to the body of knowledge on graduate employability by empirically confirming the relationship between cognitive and non-cognitive skills and employability. Prior research has explored these relationships separately; however, our research combines these elements and specifically investigates them in the context of computer science graduates. This novel integration expands the theoretical understanding of the complex interplay between cognitive skills, non-cognitive skills, and employability outcomes, addressing gaps in previous research [37], [82], [77].

Secondly, our research has identified the indirect effect of non-cognitive skills on employability via cognitive skills, a perspective that has been relatively unexplored in the employability literature. This new understanding brings attention to the pivotal role of non-cognitive skills in enhancing cognitive skills, thereby indirectly affecting employability. This multifaceted relationship underscores the need for future research to further examine the intricate dynamics among these factors [78].

Thirdly, the study demonstrates the utility and robustness of educational data mining and structural equation modeling in understanding complex educational phenomena. The application of these advanced techniques facilitates the extraction of meaningful insights from complex educational data, significantly contributing to theory development in the education field [12,81].

6.2 Practical Implications

Beyond its theoretical contributions, our study also provides several practical implications for educators, curriculum designers, policy-makers, and students in the field of computer science. By recognizing the significant roles that both cognitive and non-cognitive skills play in employability, this research calls for a reevaluation of current education practices. Curriculum designers and educators can strive to incorporate strategies to develop both these skill sets in their pedagogy. This could be achieved by implementing collaborative learning opportunities, problem-solving exercises, and real-world projects into the curriculum, thereby allowing students to simultaneously develop their technical abilities and interpersonal skills [79,83].

At the policy level, the findings of our study underline the need for comprehensive policies that advocate for the incorporation of both cognitive and non-cognitive skills training in higher education curricula. This could include encouraging pedagogical innovation, endorsing industry-academia collaborations, and incentivizing the nurturing of non-cognitive skills in students, thereby better preparing them for the dynamic demands of the workforce [84].

Lastly, for students, our findings reiterate the importance of enhancing both technical and non-cognitive skills for improved employability. As they navigate their learning journey, students can leverage these insights to focus not only on the acquisition of technical knowledge but also on developing essential non-cognitive skills that employers highly value in the competitive job market [80].

7. LIMITATIONS AND FUTURE RESEARCH

Despite the significant findings and contributions of this research, there are a few limitations that must be acknowledged. First, our study has been based on computer science graduates, thereby limiting the generalizability of the results to other disciplines. Future research could replicate this study in other fields to confirm the universality of the findings.

Second, our study has primarily focused on cognitive and non-cognitive traits, while other potential factors influencing employability such as educational environment, parental background, and societal factors were not considered. Future research can undertake a more comprehensive approach, incorporating these variables into the research model.

Third, while structural equation modeling is a powerful tool, it is primarily correlative, and causality should not be inferred from its results. Future research might employ longitudinal designs or experimental methodologies to delve deeper into the causal relationships between cognitive and non-cognitive skills and employability.

In terms of future prospects, this study paves the way for several intriguing opportunities. Given the rising prominence of remote learning and work-from-home practices, examining their impact on cognitive and non-cognitive skills and employability would be a promising direction for subsequent investigations.

Furthermore, exploring the effects of emerging technologies, such as artificial intelligence and machine learning, on employability, particularly for computer science graduates, could provide substantial insights. This could pave the way for a more holistic understanding of contemporary job market demands and the necessary skills for graduates to succeed in an increasingly digital economy.

Finally, considering the pivotal role of educators in cultivating students' cognitive and non-cognitive skills, future studies could scrutinize the teaching strategies and pedagogical practices that effectively nurture these skills, thereby further augmenting the employability of graduates.

8. CONCLUSION

The objective of this research was to develop an empirical model that could predict the employability of computer science graduates, taking into account both cognitive and non-cognitive factors. Utilizing methodologies from the field of educational data mining and structural equation modeling, the study uncovered significant correlations between cognitive abilities, non-cognitive traits, and employability outcomes. Our results emphasize that both sets of skills are integral in forecasting graduate employability, thus enhancing our understanding of the multifaceted aspects influencing employability within the computer science field.

In sum, this study offers a considerable contribution to the existing literature in the realms of education, employability, and data mining. The findings extend beyond augmenting our theoretical knowledge by delivering actionable insights for educators, curriculum developers, and policymakers. The study underlines the necessity for higher education institutions to embed strategies for the comprehensive development of both cognitive and non-cognitive abilities, thereby optimizing the employability prospects of their graduates.

While this research illuminates vital dimensions of graduate employability, it also unveils new pathways for future research, underscoring the importance of ongoing exploration in this pivotal field. As we advance into an increasingly technology-driven era, aligning our educational frameworks with the evolving dynamics of the job market becomes paramount. It is crucial to ensure that graduates are not merely employable but possess the capability to flourish within their selected career paths.

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